An Internet-Based Tool for Weather Risk Management

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This paper introduces a web-based computer program designed to evaluate weather risk management and weather insurance in the United States. The paper outlines the economics of weather risk in terms of agricultural production and household well-being; defines weather risk in terms of intensity, duration, and frequency; and illustrates the computer program use by comparing heat and precipitation risks at Ardmore, Oklahoma, and Ithaca, New York.

Key Words: weather insurance, heat insurance, precipitation insurance, crop insurance, weather derivatives

The pricing of weather insurance, and more generally the enumeration of weather risk, is not an easy task. Data are not so easily accessible, and assessing the data in terms of all of the possibilities of risk is burdensome (Campbell and Diebold 2003, Changnon and Changnon 1990). Furthermore the numbers of possibilities are virtually endless, and what might be an insurable weather risk at one location may not be insurable at another. It is for this reason that academic research has focused so heavily on the general rules of probability that govern loss and weather insurance/derivative premiums rather than on making broad generalized statements about application (Turvey 2005).

There are two gaps in the literature. The first is rudimentary. The literature on weather risk management as cited above focuses more on insurability than on how weather interacts with agricultural production and farm households as a source of risk. The idea that weather and crop yields represent covariate risks is taken as given and the effects of climate and weather variance on crop production has long been understood (Bardsley, Abey, and Davenport 1984, Changnon 2003, Huff and Neill 1982, Runge 1968). A more complete understanding of how covariate risks evolve in a production system, even at the conceptual level, can provide invaluable insights to the practitioner and theorist. In this paper we present such a model. It is not a precise model, nor are we in a position to empirically validate the model, but it does provide the requisite insight to understanding covariate risk and how covariate risks interact with farm livelihoods to create an insurable condition.

The second gap, and the focal point of this paper, is the measurement of weather risk and the insurability of weather risk. Despite recent interest in weather insurance, the idea of insuring weather risk as an alternative to crop insurance is not new (several articles predating 2000 that made such propositions include Changnon and Changnon 1990, Gautman, Hazell, and Alderman 1994, Quiggen 1986, Patrick 1998, Sakurai and Reardon 1997). Since 2000, a variety of weather insurance models, propositions, theorems, and structures have been proposed, but there is little agreement on how weather risk should be defined or how weather insurance should be priced [Alaton, Djehiche, and Stillberger 2002, Alderman and Haque 2006, Cao and Wei 2004, Considine (undated), Davis 2001, Dischel 2002, Geman 1999, Jewson and Brix 2005, Leggio and Lien 2002, Muller and Grandi 2000, Nelken 1999, Richards,

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Manfredo, and Sanders 2004, Turvey 2001, Turvey 2005, Zeng 2000]. Applications of weather insurance in North America, Europe, and developing economies are varied and include numerous important contributions to a range of issues including agricultural production risk, food security, poverty alleviation, irrigation insurance, intertemporal risks, and so on (Alderman and Haque 2006, Hao and Skees 2003, Hazell, Oram, and Chaherli 2001, Hazell and Skees 2006, Hess, Richter, and Stoppa 2002, Lacoursiere 2002, Leiva and Skees 2005, Mafoua and Turvey 2003, Martin, Barnett, and Coble 2001, Muller and Grandi 2000, Skees, Hartell, and Hao 2006, Skees et al. 2001, Stoppa and Hess 2003, Turvey, Weersink, and Chiang 2006, Vedenov and Barnett 2004, Veeramani, Maynard, and Skees 2003).

Part of the problem is that use of the term "weather risk" is far too ubiquitous, and agricultural economists seeking agreement on a definition of weather risk will ultimately be disappointed. As will be discussed presently, the term implicitly includes considerations of frequency, intensity, and duration. The gap extends when one asks "what risk?" and expands even further when one tries to determine, evaluate, or measure the risk. It is no easy task, and perhaps too much of the academics' energy is used on measuring the risk rather than defining the risk and applying the risk. This is at the core of this paper. In this paper we describe a web-based application program called WeatherWizard[1] that was developed along the lines of Turvey (2001) for specific event temperature and precipitation risks and Turvey (2005) for degree-day temperature risk. The program accesses heat and precipitation data for all NOAA weather stations (currently available through 2001) in the United States and can be used to investigate weather-related risk and calculate insurance for virtually all possible single and multiple specific events.

The main contribution of this research is the outreach tool itself. WeatherWizard can be accessed by researchers, crop insurance specialists, educators, and practitioners. In a very short period of time—measured in minutes rather than days or weeks—the user can select any location, define a specific event, and enumerate that risk. Furthermore, users can evaluate up to five joint precipitation and temperature risks as well as basis risk for a specific weather event for all weather stations within 50 miles of a specific location.

The paper proceeds as follows. First we provide a conceptual overview of weather risk in the theory of production. Second, we focus on the meaning of "weather risk," and then we describe in general terms the underlying philosophy of the computer program and the meaning of specific event risk. Following our conclusions, in the Appendix the program is illustrated in terms of screen displays and application.

Economics and Weather Risk

The central focus of this paper is the presentation of a web-based computer program designed for the measurement of weather risk. To motivate the need for such a program, this section outlines the relationships between production economics, weather risk, and farm livelihoods to show how specific weather events interact as a source of risk and how these risks can be mitigated using weather insurance. We make two assumptions. First we assume that the specific weather event is treated as a stochastic input into the production function, and second we assume that livelihood is measured in the context of a whole farm or household production function. We do not assume a stochastic production function that simply adds randomness to a deterministic function. Rather, we assume that the weather event creates randomness in the production coefficients themselves so that marginal productivity is endogenously random. Keeping in mind that any production function will do, we start with a classical form of production:

$$(1) \qquad Y\left(x,\bar{\omega}\right)=\alpha_1\left(\bar{\omega}\right)+\alpha_2\left(\bar{\omega}\right)x\text{-}\alpha_3\left(\bar{\omega}\right)x^2,$$

where x is an ordinary input (e.g., fertilizer), and $\alpha_i(\ )$ are random coefficients of the production function. If one were to assume that $\alpha_i(\omega) = \alpha_i + \beta_i\omega + \varepsilon_i$ is a function of some specific weather event ω defined over some (known or unknown) probability distribution function that describes the specific event risk, then the stochastic production function is

[1] See www.weatherwizard.us.

$$(2)\quad Y(x,\omega)=\alpha_1+\beta_1\omega+(\alpha_2+\beta_2\omega)x \\ -(\alpha_3+\beta_3\omega)x^2+\varepsilon_1+\varepsilon_2 x-\varepsilon_2 x^2,$$

with expected production being

$$(3)\quad E\left[Y(x,\overline{\omega})\right]=\alpha_1+\beta_1\overline{\omega}+(\alpha_2+\beta_2\overline{\omega})x \\ -(\alpha_3+\beta_3\overline{\omega})x^2.$$

Under the independence assumption, yield variance, conditional on weather risk, is defined by

$$(4)\quad \sigma_Y^2=\left(\beta_1^2\sigma_\omega^2+\sigma_{\varepsilon_1}^2\right)+\left(\beta_2^2\sigma_\omega^2+\sigma_{\varepsilon_2}^2\right)x^2 \\ +\left(\beta_3^2\sigma_\omega^2+\sigma_{\varepsilon_3}^2\right)x^4.$$

In words, the standard errors of the production coefficients comprise two influences. The first, we argue, is the influence of weather risk, and the second is an unrelated risk. It is of course assumed that if weather insurance is to be viable as a risk management tool, then the portion of the standard error attributable to weather must be significantly and proportionately higher than the non-systematic risk component. In any case, weather risk influences the production of agricultural products by causing a shift in the location of the production function as well as its slope and shape, and the nature of these risks is contingent on the ex ante choice of x. This choice will be based upon average or expected evolution of crop-specific weather events throughout the growing season. The interaction of ideal weather events with optimum input levels can lead, ex post, to higher yields and marginal productivity, while poor weather interacts to reduce marginal productivity and yields. In other words, the production function coefficients are random, and the final yield depends on the specific weather event conditional on the initial deterministic choice of x.

The effect on total productivity due to a change in ω from its mean is

$$(5)\quad \frac{\partial Y(x,\overline{\omega})}{\partial\omega}=\frac{\partial\alpha_1(\omega)}{\partial\omega}+\frac{\partial\alpha_1(\omega)}{\partial\omega}x-\frac{\partial\alpha_1(\omega)}{\partial\omega}x^2.$$

Because ω is a random variable, the ex post distribution of crop yields would appear as

$$(6)\quad Y(\omega\mid x)=\int_u^l Y(\omega)f(\omega)\,d\omega.$$

The marginal product function of $Y(x,\overline{\omega})$ is given by

$$(7)\quad \frac{\partial Y(x,\overline{\omega})}{\partial x}=\alpha_2(\overline{\omega})-2\alpha_3(\overline{\omega})x,$$

and basing ex ante input choice on the expected value of ω, the expected yield-maximizing choice of input is

$$x^*=\frac{\alpha_2(\omega)}{2\alpha_3(\omega)}.$$

In reality, the actual marginal productivity of x is a stochastic function,

$$(8)\quad \frac{\partial^2 Y(x,\overline{\omega})}{\partial x\partial\omega}=\frac{\partial\alpha_2(\omega)}{\partial\omega}-2\frac{\partial\alpha_3(\omega)}{\partial\omega}x,$$

which can also be expressed as a conditional marginal product function,

$$(9)\quad \mathrm{MPP}(\omega\mid x^*)=\int_{\mathrm{u}}^{1}\frac{\partial Y(\omega\mid x^*)}{\partial\omega}f(\omega)\,d\omega.$$

In other words, weather is not simply a passive actor in agricultural productivity, but can change not only the total productivity by shifting the production function up or down, but also the marginal productivity. Nor is it a simple distribution about some level of expected yields, but a factor that can change the shape of the production function throughout the range of x. The efficiency of production is also at risk. Given a prior choice of x and no bounds on

$$\alpha_i(\omega),\ \frac{\partial^2 Y(x,\overline{\omega})}{\partial x\partial\omega}<=>0,$$

ex post production relative to input choice can exhibit increasing, constant, or diminishing returns to scale, even though in the deterministic model, only diminishing marginal productivity would be observed.

We now define a weather-contingent livelihood function that can be thought of as a stochastic household production function. Its general form is given by

$$(10)\quad H[Y(\omega),\omega] = \int_l^u h[Y(\omega),\omega] f(\omega) d\omega .$$

Weather risk enters the livelihood function in two ways. First, as discussed above, agricultural productivity is affected directly by weather risk, but other aspects of livelihood can also be affected. For example, if the farm is financially leveraged, short on working capital, or requires investment, liquidity shortfalls from adverse weather events can have economic impacts beyond production. Thus the more flexible form of weather risk management is not necessarily tied to agricultural productivity, but household livelihood. From this we can extract the coverage for a specific weather event by extracting from $H(\omega)$ the value for ω that satisfies a minimal livelihood level $\widehat{H}(\omega^*)$, $\omega^* = \widehat{H}^{-1}(\omega)$. Therefore, a downside weather risk policy will be established according to

$$(11)\quad \mathrm{E}\left\{\mathrm{Max}\left[\widehat{H} - H, 0\right]\right\} = \psi \mathrm{E}\left\{\mathrm{Max}\left[\omega^* - \omega, 0\right]\right\},$$

where ψ converts units of weather into units of currency. A convenient measure is

$$\psi = \frac{\widehat{H}}{\omega^*}.$$

It is this interaction between production and farm household well-being that motivates weather risk as an area of study and makes weather insurance useful. However, the actual measurement of weather risk is not easily accomplished. The characteristics of weather risk are discussed in the next section, and the tool developed to measure weather risk and weather risk insurance follows.

Frequency, Duration, and Intensity of Specific Weather Events

The preceding discussion uses the term "weather risk" in a very general way. It is in fact more complex than a simple definition of a random variable as described. The intent above was to provide a conceptual basis for the measurement of risks that follows. For purposes of this paper and the description of WeatherWizard, we will use for determining the expectation of loss the working definition that a specific event risk is uniquely defined at any location by the functional relationship between duration, frequency, and intensity. Duration is a definition in time ranging from a day, week, month, year, or more or less. The model additionally uses the concept of multiple events, which implies a second dimension of time. The first dimension therefore measures the period over which the weather event is to be investigated, while the second dimension is a time frame within that period. For example, duration could be measured by any non-overlapping 21-day period between June 1 and August 31. There is a possibility of four non-overlapping events. If the event were measured on a 7-day basis, there could be as many as 12 non-overlapping events.

Frequency measures the probability scale defined in terms of the frequency that the event occurs over the specified duration. Frequency here can be based on historical fact (often referred to as the burn rate) or by a defined distribution (e.g., an assumption of log normality).

Intensity is a measure of scale and refers to the quality or condition under investigation and thus requires a point of reference from which quality can be measured and a directional indicator by which condition can be measured. The former will usually be measured by a quantitative criterion such as rainfall or temperature, and the condition is normally defined by whether the actual quantity is above or below the point of reference.

But the terms in their totality must remain flexible. For example, a degree-day derivative product is normally defined for a single event in which the event length equals the period over which the product is being measured. Extreme heat or heat waves regarded as a sequential number of days over which daily temperatures exceed a criterion can be defined as multiple events. Likewise, precipitation events based on daily or cumulative precipitation can be multiple or single events, and so on.

Care must also be taken in establishing the criteria. Specificity is important. For example, we do not in any of our models facilitate insurance or risk management in terms of averages, because averages, unto themselves, are meaningless. Specific events as we have defined them are based wholly on the sequencing and timing of weather patterns, for which full information on the frequency, duration, and intensity is required.

The final element is loss value. Unlike crop insurance, for which a measured loss can be ascertained by the actual weight of crop harvested times a price, the loss value from yield-independent weather risk is less obvious. By "yield-independent" we mean that any payout from weather insurance is provided based on recognized weather measurements at specific weather stations rather than yield loss. It is of course assumed that there is some a priori recognition that the weather event will be highly correlated with yield loss and that the loss value can be estimated or approximated so that volumetric loss is approximated more or less. This might allow for some speculation on the part of the insured, but such speculation does not constitute moral hazard or adverse selection as it is normally construed in the insurance literature, since the premium calculated is actuarially consistent with the weather event. Nonetheless, it serves little purpose to even consider specific events near the average since such insurance will ultimately be expensive and largely uncorrelated with yield loss. Rather, weather insurance should focus on events of the extreme, which, at least within the realm of memoried probability, would most surely result in volumetric and economic loss. For example, it makes little sense for an insured to select a contract insuring against a heat wave based on daily high temperatures in excess of 75°F when loss does not occur until temperatures exceed 90°F, or a contract insuring against less than 1 inch of cumulative rain over 7 days when it is known that the crop can withstand 21 days with no or little rain.

On this basis we use two dollar-valued measurements. The first is a lump sum or binary payout, which simply pays an agreed sum if the event occurs (regardless of intensity) and zero otherwise. The second is a unit payout, similar to options payouts or crop insurance payments in which the payout for each event increases linearly with intensity. The binary option is simple and convenient and is most applicable when the event itself, rather than the intensity of the event, is what causes risk. For example, it matters not whether a frost event is measured at 31°F or 20°F—the damage is still done; or if it rains less than 2 inches in 21 days, irrigation costs will still be incurred whether rainfall is 0.5 inches or 1.99 inches. The unit payout is most useful when volumetric losses are known to increase with intensity—for example, when crop losses increase proportionately (or approximately so) as crop heat units fall below or rise above the boundaries of normal crop heat units, or losses increase as cumulative rain falls below a stated quantity, and so on.

Assessing Weather Risk and Weather Risk Insurance with WeatherWizard

We provide in the Appendix screen shots of the WeatherWizard program. In this section we provide, as a matter of illustration, heat and precipitation insurance results obtained entirely from WeatherWizard. We use for our example the city of Ardmore, Oklahoma (Carter County), which has continuous daily heat and precipitation data from 1902 to 2001. Perhaps more than this is its location between Oklahoma City and Dallas, Texas, which places it centrally in the areas affected by the Dust Bowl activity of the 1930s, providing thus a historical perspective on extreme weather events that is represented by the data and which will be familiar to most readers. We compare this to weather risk recorded at Cornell University at Ithaca in central New York.

Heat Insurance

Insurance based on heat is far more common in the energy industry than found in agriculture, but for many agricultural commodities extreme heat can cause volumetric decline in yield, quality loss, energy consumption, and livestock death. The events we speak of are not ordinary events but, as indicated above, extreme events that persist for extended periods of time.

Table 1 provides a summary of degree-days for Ardmore and Ithaca. Recall that degree-days in the energy industry are measured relative to 65°F and corn heat units relative to 50°F, but this need not be viewed as a meaningful economic standard. Heat stress in agriculture does not in most cases occur until temperatures are well in excess of 80°F, so it makes little sense to include temperatures below the stress levels. But stress must also be measured relative to climate. The degree-days measured in Table 1 are obtained by adding together the difference between the (91) daily high temperatures in excess of the degrees identified in the first column. The mean degree-days are provided in column 2, the standard deviation across years in column 3, and the historical maxi-

Table 1. Historical Degree-Day Comparison for Ardmore, OK, and Ithaca, NY, June 1–August 31

Degree-Day Based on Degrees Fahrenheit (F)	Degree-Days	Standard Deviation	Maximum	Minimum
		ARDMORE, OKLAHOMA		
80°	1269	246	1909	520
85°	837	233	1454	344
90°	458	201	1007	84
95°	184	137	595	0
100°	48	57	247	0
		ITHACA, NEW YORK		
80°	218	111	508	26
85°	67	58	235	2
90°	13	19	83	0
95°	1.4	4.23	27	0
100°	0.14	0.76	6	0

Note: Degree-day measures based on temperatures above daily high temperatures ranging from 80°F to 100°F.

mums and minimums in columns 4 and 5. For the same temperature measures the degree-days are strikingly different between Ardmore and Ithaca. In Ardmore, a southern location, for example, the average degree-days based on 90°F is 458 with a standard deviation of 201, but for Ithaca it is only 13 with a standard deviation of 19. Clearly, any heat insurance policy designed for Ithaca is not applicable to Ardmore.

WeatherWizard in fact was designed with such differences in mind. Weather insurance cannot be applied in an ad hoc fashion, but must be computed at each individual location. The effect is seen in Table 2 which provides premiums for an 85°F degree-day excess heat contract for June 1 through August 31 for Ardmore and Ithaca. Not only are insurance strike or coverage levels evaluated at Ithaca irrelevant to the climatic conditions at Ardmore, but the cost differences are also significant. Given the range of degree-days in Table 1 for 85°F, it makes little sense to consider insurance that is close to the mean for it is unlikely that economic damage would be significant at that level. In addition, to choose a strike of, say, 1,000 for Ardmore or 100 for Ithaca comes at such a high cost because at these levels some amount of payment will appear in almost every year. It is the extreme events with low probability but high economic loss that matter. In Ardmore, considering such insurance at a strike of 1,350 or higher, or in Ithaca of 200 or higher, would probably be more sensible. This discussion also raises the issue of what is an extreme event. Is it a 1 in 100 year event, 1 in 50 year event, or 1 in 10 year event? There is no set answer but WeatherWizard can be used to identify the risks.

The use of degree-days as a measure of risk represents a broad seasonal measure of risk. It is specific only to the time frame in question (e.g., June 1 through August 31) and represents more or less the intensity of broad temperature risks such as a summer that is hotter than usual or cooler than usual. An alternative approach is to examine specific events. Table 3 presents results for the specific event of a heat wave in which the daily high temperature exceeds 90°F for N consecutive days (the event length). WeatherWizard can also compute risks of multiple events. For example, for a 7-day heat wave there are 13 possible non-overlapping 7-day events, and for a 35-day heat wave there are only 2. The results in Table 3 are based on the maximum possible events. Again, one must rethink what constitutes a heat wave. A 7-day event will occur at least once a year in

Table 2. Degree-Day Heat Insurance Premiums Based on 85°F Degree-Days ($1,000/degree) for Strike Levels of 850–1,400 Degree-Days

Ardmore, Oklahoma		Ithaca, New York	
Strike	Premium	Strike	Premium
850	89,520	50	30,041
900	70,270	75	20,054
950	53,739	100	13,514
1,000	40,307	125	8,518
1,050	29,818	150	4,730
1,100	21,473	175	2,108
1,150	15,224	200	797
1,200	9,974	225	135
1,250	5,943		
1,300	3,339		
1,350	1,615		
1,400	573		

Table 3. Multiple Event Heat-Wave Frequencies (events per 100 years) Based on Daily High Temperatures Exceeding 90°F for N Consecutive Days and Showing Risk Differences Between Ardmore and Ithaca

		Frequency of Events				
Event Length (days)	Premium	Percent 0 Events	Percent 1 Event	Percent 2 Events	Percent 3 Events	Percent 4 or More Events
Ardmore, Oklahoma						
7	7,469	0	0.0104	0.0208	0.0417	0.9271
14	2,729	0.0625	0.1042	0.2604	0.2708	0.3021
21	1,427	0.1667	0.3958	0.2917	0.1354	0.0104
28	823	0.375	0.4355	0.1771	0.0104	0
35	510	0.5521	0.3854	0.0625	0	0
Ithaca, New York						
2	1,865	0.405	0.162	0.176	0.054	0.203
3	757	0.608	0.189	0.122	0.014	0.067
4	324	0.77	0.162	0.041	0.027	0
5	95	0.92	0.068	0.014	0	0
6	68	0.93	0.07	0	0	0
7	27	0.97	0.03	0	0	0
8	14	0.99	0.01	0	0	0

Ardmore, and in fact there is a 92.71 percent chance of four or more such events, but a 7-day event in Ithaca is extremely rare, occurring only 3 of every 100 years. Likewise, a 9-day heat wave has never occurred in Ithaca (given the data available), but in Ardmore in 38 of every 100 years there is a possibility that daily high temperatures will exceed 90°F for 35 straight days, and in 6 of every 100 years this could occur twice.

When considering weather insurance one must also consider how agriculture has adapted to the climates in each region. Irrigated cotton and wheat in southern Oklahoma is an agricultural adaptation to that region's climate as much as dairy, orchards, grapes for vines, corn, and soybeans are an adaptive response to the climate of the northeast. Furthermore, grain and oilseed hybrids have been developed for specific heat units that are adaptive to a region's climate. It is when climate exceeds the bounds of adaptation that weather insurance is most valuable.

Precipitation Insurance

WeatherWizard also calculates an array of specific-event risks based on precipitation. Again, regional adaptability and differences need to be considered. Table 4 illustrates premiums and risk for cumulative rainfall between June 1 and August 31. This is a 91-day event and is the most basic of precipitation insurance contracts. There are two insurance calculations in Table 4. The first is that if the event happens then a $1,000 payment would be made. The second is based on a unit payout, which means that a payment is made on the positive difference between the coverage level and actual cumulative rainfall only. For this reason the lump-sum insurance is more expensive at lower precipitation levels and less expensive at higher precipitation levels.

In Ardmore the cumulative rainfall is 9.08 inches with a standard deviation of 4.57 inches, while in Ithaca the average cumulative rainfall is 10.74 inches with a standard deviation of 2.77 inches. Clearly, rainfall is less prevalent and more variable in southern Oklahoma than in central New York. Furthermore, southern Oklahoma is far more drought-prone than central New York, with a 1 in 100 year event of less than 2 inches of rain over the 91-day period, and a 30.3 percent chance of cumulative rain falling below 5 inches. In contrast, the data available for Ithaca indicates that in no year did cumulative rainfall fall below 5 inches. In Ardmore there is a 57.58 percent chance of less than 9 inches of rainfall, but in Ithaca the chance is only 31.08 percent. For this reason the insurance cost for drought insurance is much higher in Ardmore than Ithaca, and again one must consider the practicality of offering drought insurance in an area prone to drought.

Table 5 provides examples of specific event risks for different risk criteria. The values are premiums based on lump sum and unit payouts as well as the maximum number of possible events. Here the specific event risk is defined by event lengths from 7 to 42 days. Close examination of the results indicate the significance of the timing and sequencing of rainfall in determining insurance premiums for specific event risks. Reading across the rows it is clear that the cost of precipitation insurance will increase as the event criteria increases. Insuring against receiving less than 0.25 inches in any 21-day period will cost only $104, $636, $19.50, and $162, in comparison to a policy with a 2-inch requirement costing $3,071, $2,828, $416, and $2,541. This is simply reflecting the fact that it is far less likely that cumulative rainfall will be less than 0.25 inches than rainfall would be less than 2.0 inches. Looking down each column reflects the temporal risk. It is far more likely that rainfall in any 7-day period will be less than 0.25 inches than in any 42-day period.

Summary

Space constrains all the possible considerations for weather insurance and weather risk management with WeatherWizard. The degree-day derivative worksheet, for example, was not presented in this paper, but a word on the pricing of degree-day insurance using the Black-Scholes model is warranted. The algorithm underlying the degree-day "derivative" approach is outlined in Turvey (2005), and in that paper considerable space is dedicated to a reasoned comparison of a number of methods, including that proposed by Richards, Manfredo, and Sanders (2004). It is not the final word for sure, for there is still considerable debate on the role of the market price of risk [assumed zero in Turvey (2005)] and the use of equilibrium pricing models in general.

Having said that, the intent of this paper was not to provide the mathematical or structure of weather insurance or derivative pricing, but to

Table 4. Seasonal Cumulative Precipitation Insurance Premiums, 91 Days, June 1–August 31, for Lump-Sum and Unit Payouts ($1,000/inch)

	Ardmore, Oklahoma			Ithaca, New York		
Average	9.08″			10.74″		
Std Dev	4.57″			2.77″		
Less than ...	Lump Sum	Unit Payout	Frequency	Lump Sum	Unit Payout	Frequency
2″	10.10	0.30	0.0101	0	0	0
3″	50.51	26.26	0.0505	0	0	0
4″	101.01	97.37	0.101	0	0	0
5″	212.12	246.77	0.2121	0	0	0
6″	303.03	487.78	0.303	13.51	2.97	0.0135
7″	383.84	838.48	0.3838	81.08	50.81	0.0811
8″	474.75	1276.06	0.4747	162.16	167.3	0.1622
9″	575.76	1798.28	0.5758	310.81	408.51	0.3108

present a tool that can be used to investigate specific event weather risks and to price the value of mitigating such risk. Not presented in this paper are newer developments to the program that include two new algorithms. The first follows through on the definition of risk. In many circumstances yield loss may not be due to a single event but to joint events. Rust, nematodes, molds, and insect infestations often arise from combined events such as a wet spring followed by a cool summer, or a dry spring followed by a hot summer, and so on. Again the risk combinations are specific. As of the time of this writing, up to five separate events could be defined and the joint probabilities assessed. We believe that measuring intertemporal covariate risks such as excess heat jointly with rainfall shortfalls by season or event is clearly the next step in designing insurance instruments to manage weather risks.

The second innovation not presented in this paper is the evaluation of basis risk. At the time of writing, this particular algorithm was near completion. It too is important. One of the major concerns with weather insurance is the problem of basis risk, which refers to the risk differential between a defined location such as a farm, and the point of measurement or weather station. If there is too much variability across space and time, then weather insurance may not capture the true intended covariate risk. The WeatherWizard algorithm defines a radius of up to 100 miles around a given location (zip code) and identifies all weather stations within the defined circle. The weather station locations can be viewed using Google Earth. Furthermore, a regression algorithm using the basis difference between the central location and the weather stations as the dependent variable, and distance, altitude difference, and directional indicators (e.g., NW, NE, etc.) is included to provide an explanation for the basis risks.

Finally, the emergence of weather risk management through insurance or derivative instruments has given rise to a different perspective on risk and risk management. In production economics the measurement of yield risk defined by mean and variance is no longer standard practice. The impact of risks in the extreme and covariate risk should now be defined by specific events, and this is no trivial matter. As illustrated in the heat and precipitation examples at Ardmore, Oklahoma, and Ithaca, New York, specific event risks are such that between any two locations comparison is useful for academic and policy purposes only. As a practical matter, no common statement of risk between the two locations can reasonably be asserted; the timing and sequencing and frequency of specific weather event risks in Ardmore will have a totally different effect on the production economy than the timing and se-

Table 5. Multiple Event Cumulative Rainfall Insurance ($1,000 lump sum or $1,000/inch)

Event Length (days)	0.25″	0.50″	0.75″	1.00″	1.50″	2.0″
ARDMORE, OKLAHOMA—UNIT PAYOUT						
7	1,584	3,369	5,341	7,380	11,809	16,505
14	504	1,141	1,824	2,626	4,430	6,361
21	224	521	876	1,200	2,162	3,071
28	104	239	418	609	1,064	1,588
35	63	150	247	362	633	952
42	23	57	96	186	346	589
ARDMORE, OKLAHOMA—LUMP SUM PAYMENT						
7	7,828	8,565	9,182	9,626	10,111	10,424
14	2,798	3,293	3,747	4,162	4,566	4,949
21	1,354	1,687	1,990	2,222	2,566	2,828
28	636	869	1,080	1,313	1,485	1,808
35	384	525	687	798	1,050	1,253
42	162	232	354	475	707	879
ITHACA, NEW YORK—UNIT PAYOUT						
7	784	2,061	3,718	5,712	10,501	16,124
14	101	319	713	1,051	2,391	4,153
21	19.5	64	158	245	663	1,304
28	7.3	16	43	67	202	416
35	2.03	6	13	15	57	157
42	2.03	5	9	0.41	22	53
ITHACA, NEW YORK—LUMP SUM PAYOUT						
7	5,635	7,919	9,365	10,351	11,675	12,351
14	838	1,675	2,581	3,243	4,473	5,257
21	162	432	676	1,000	1,932	2,541
28	54	81	203	324	730	1,203
35	14	27	54	81	230	486
42	14	14	14	27	95	189

quencing and probability of the same specific event risk defined at Ithaca. This new frontier in risk management demands specificity over generalization in order to be meaningful. It is with this in mind that WeatherWizard was developed.

References

Alaton, P., B. Djehiche, and D. Stillberger. 2002. "On Modeling and Pricing Weather Derivatives." *Applied Mathematical Finance* 9(1): 1–20.

Alderman, H., and T. Haque. 2006. "Insurance Against Covariate Shocks: The Role of Index-Based Insurance in Social Protection in Low-Income Countries of Africa." Africa Region Human Development Group, World Bank, Washington, D.C.

Bardsley, P.A., A. Abey, and S. Davenport. 1984. "The Economics of Insuring Crops Against Drought." *Australian Journal of Agricultural Economics* 28(1): 1–14.

Campbell, S.D., and F.X. Diebold. 2003. "Weather Forecasting for Weather Derivatives." NBER Working Paper No. 10141, National Bureau of Economic Research, Cambridge, MA.

Cao, M., and J. Wei. 2004. "Weather Derivatives Valuation and the Market Price of Weather Risk." *Journal of Futures Markets* 24(11): 1065–1089.

Changnon, S.A. 2003. "Measures of Economic Impacts of Weather Extremes: Getting Better But Far from What Is Needed—A Call for Action." *Bulletin of the American Meteorological Society* 84(9): 1231–1235.

Changnon, S.A., and J.M. Changnon. 1990. "Use of Climatological Data in Weather Insurance." *Journal of Climate* 3(2): 568–576.

Considine, G. (undated). "Introduction to Weather Derivatives." Working paper, Chicago Mercantile Exchange, Chicago, IL.

Davis, M. 2001. "Pricing Weather Derivatives by Marginal Value." *Quantitative Finance* 1(3): 305–308.

Dischel, R.S. (ed.). 2002. *Climate Risk and the Weather Market*. London: Risk Books.

Gautman, M., P. Hazell, and H. Alderman. 1994. "Management of Drought Risks in Rural Areas." Policy Research Working Paper No. 1383, World Bank, Washington, D.C.

Geman, H. (ed.). 1999. *Insurance and Weather Derivatives: From Exotic Options to Exotic Underlyings*. London: Risk Books.

Hao, J., and J.R. Skees. 2003. "Structuring Institutions to Share Local Weather Risks Globally." Selected paper, American Agricultural Economics Association's annual conference, Montreal, Québec.

Hazell, P., P. Oram, and N. Chaherli. 2001. "Managing Droughts in the Low-Rainfall Areas of the Middle East and North Africa." EPTD Discussion Paper No. 78, International Food Policy Research Institute (IFPRI), Washington, D.C.

Hazell, P., and J.R. Skees. 2006. "Insuring Against Bad Weather: Recent Thinking." In R. Radhakrishna, S.K. Rao, S. Mahendra Dev, and K. Subbarao, eds., *India in a Globalizing World: Some Aspects of Macroeconomy, Agriculture, and Poverty*. New Delhi: Academic Foundation.

Hess, U., K. Richter, and A. Stoppa. 2002. "Weather Risk Management for Agriculture and Agribusiness in Developing Countries." In R.S. Dischel, ed., *Climate Risk and the Weather Market: Financial Risk Management with Weather Hedges*. London: Risk Books.

Huff, F.A., and J.C. Neill. 1982. "Effects of Natural Climatic Fluctuations on the Temporal and Spatial Variation in Crop Yields." *Journal of Applied Meteorology* 21(4): 540–551.

Jewson, S., and A. Brix. 2005. *Weather Derivative Valuation: The Meteorological, Statistical, Financial and Mathematical Foundations*. Cambridge, UK: Cambridge University Press.

Lacoursiere, C. 2002. "Canada Opens New Pastures." *Energy Risk* ("Special Report: Weather Risk," August 2002).

Leggio, K.B., and D. Lien. 2002. "Hedging Gas Bills with Weather Derivatives." *Journal of Economics and Finance* 26(1): 88–100.

Leiva, A., and J. Skees. 2005. "Managing Irrigation Risk with Inflow-Based Derivatives: The Case of Rio Mayo Irrigation District in Sonora, Mexico." Selected paper, American Agricultural Economics Association's annual conference, Providence, RI.

Mafoua, E., and C.G. Turvey. 2003. "Weather Insurance to Protect Specialty Crops Against Costs of Irrigation in Drought Years." Selected paper, American Agricultural Economics Association's annual conference, Montreal, Québec.

Martin, S.W., B.J. Barnett, and K.H. Coble. 2001. "Developing and Pricing Precipitation Insurance." *Journal of Agricultural and Resource Economics* 26(1): 261–274.

Muller, A., and M. Grandi. 2000. "Weather Derivatives: A Risk Management Tool for Weather Sensitive Industries." *The Geneva Papers on Risk and Insurance* 25(1): 273–287.

Nelken, I. 1999. "Weather Derivatives—Pricing and Hedging." Super Computer Consulting Inc., Mundelein, IL.

Patrick, G.F. 1998. "Mallee Wheat Farmers' Demand of Crop and Rainfall Insurance." *Australian Journal of Agricultural Economics* 32(1): 37–49.

Quiggen, J. 1986. "A Note on the Viability of Rainfall Insurance." *Australian Journal of Agricultural Economics* 30(1): 63–69.

Richards, T.J., M.R. Manfredo, and D.R. Sanders. 2004. "Pricing Weather Derivatives." *American Journal of Agricultural Economics* 86(4): 1005–1017.

Runge, E.C.A. 1968. "Effects of Rainfall and Temperature Interactions During the Growing Season on Corn Yield." *Agronomy Journal* 60(5): 503–507.

Sakurai, T., and T. Reardon. 1997. "Potential Demand for Drought Insurance in Burkina Faso and Its Determinants." *American Journal of Agricultural Economics* 79(4): 1193–1207.

Skees, J., S. Gober, P. Varangis, R. Lester, and V. Kalavakonda. 2001. "Developing Rainfall-Based Index Insurance in Morocco." World Bank Policy Research Working Paper No. 2577, World Bank, Washington, D.C.

Skees, J.R., J. Hartell, and J. Hao. 2006. "Weather and Index-Based Insurance for Developing Countries: Experience and Possibilities." In A. Sarris and D. Hallam, eds., *Agricultural Commodity Markets and Trade: New Approaches to Analyzing Market Structure and Instability*. Northampton, MA: Edward Elgar.

Stoppa, A., and U. Hess. 2003. "Design and Use of Weather Derivatives in Agricultural Policies: The Case of Rainfall Index Insurance in Morocco." Paper contributed at the "Agricultural Policy Reform and the WTO: Where Are We Heading?" conference in Capri, Italy, June 23–26.

Turvey, C.G. 2001. "Weather Derivatives for Specific Event Risks in Agriculture." *Review of Agricultural Economics* 23(2): 333–351.

____. 2005. "The Pricing of Degree-Day Weather Options." *Agricultural Finance Review* 65(1): 59–86.

Turvey, C.G., A.J. Weersink, and C. Chiang. 2006. "The Feasibility of Ice Wine Insurance for Ontario Ice Wine Producers." *American Journal of Agricultural Economics* 88(3): 696–709.

Vedenov, D.V., and B.J. Barnett. 2004. "Efficiency of Weather Derivatives as Primary Crop Insurance Instruments." *Journal of Agricultural and Resource Economics* 29(3): 387–403.

Veeramani, V.N., L.J. Maynard, and J.R. Skees. 2003. "Assessment of Risk Management Potential of Rainfall Based Insurance Index and Rainfall Options in Andhra, India." Selected paper, American Agricultural and Resource Economics' annual conference, Montreal, Québec.

Zeng, L. 2000. "Pricing Weather Derivatives." *Journal of Risk Finance* 1(3): 72–78.

APPENDIX: The WeatherWizard Program

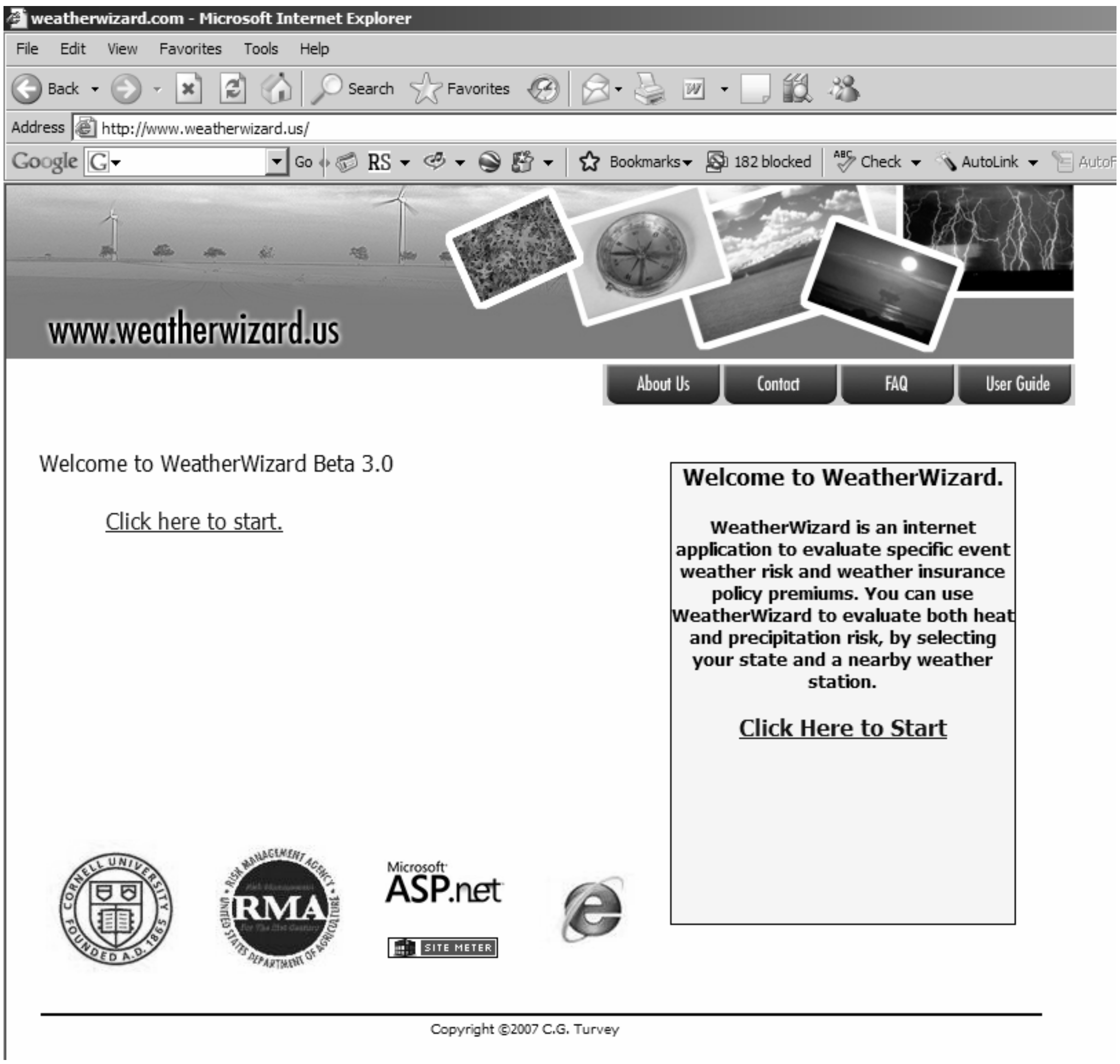


Figure A1. WeatherWizard Main Screen

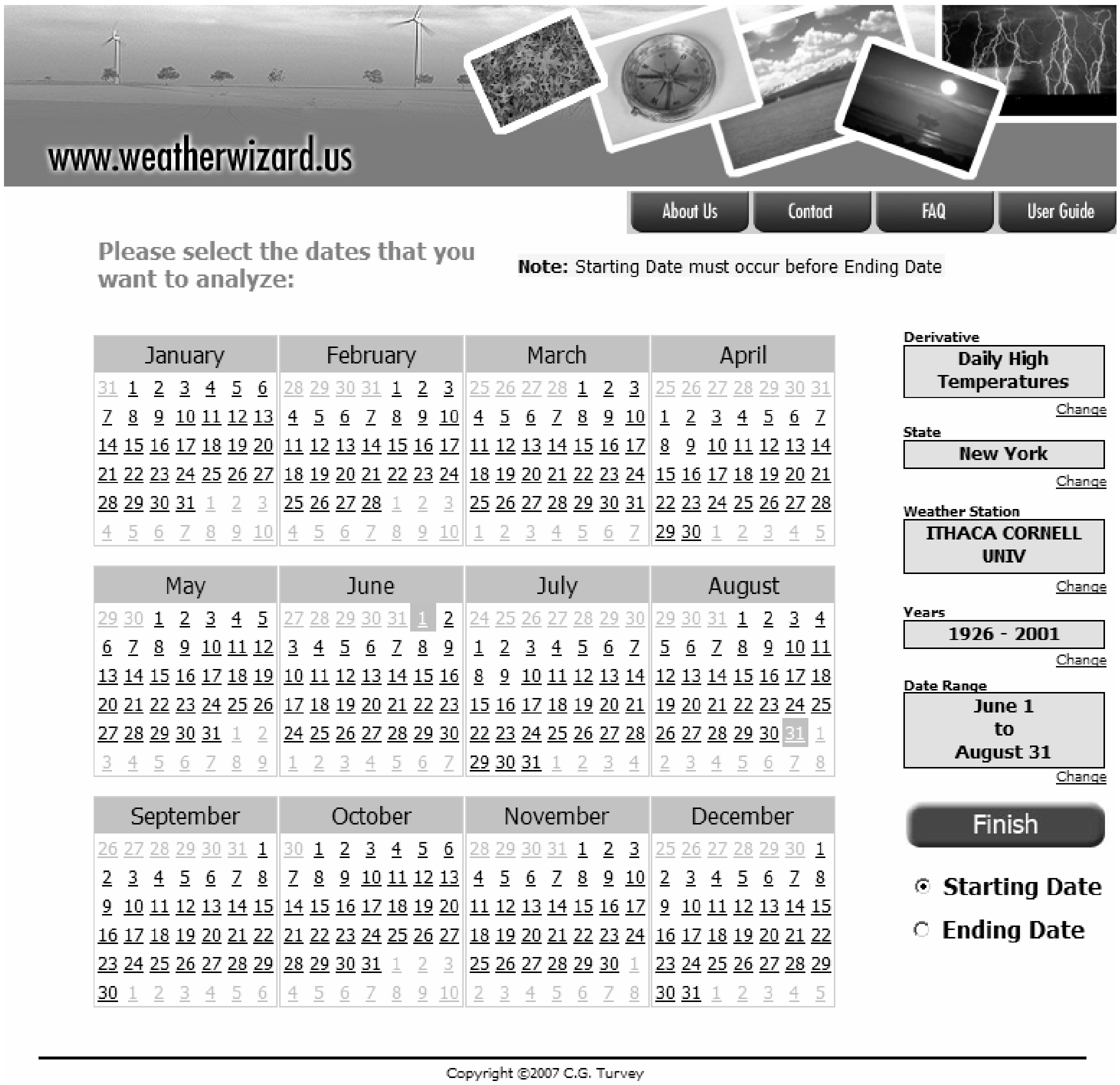
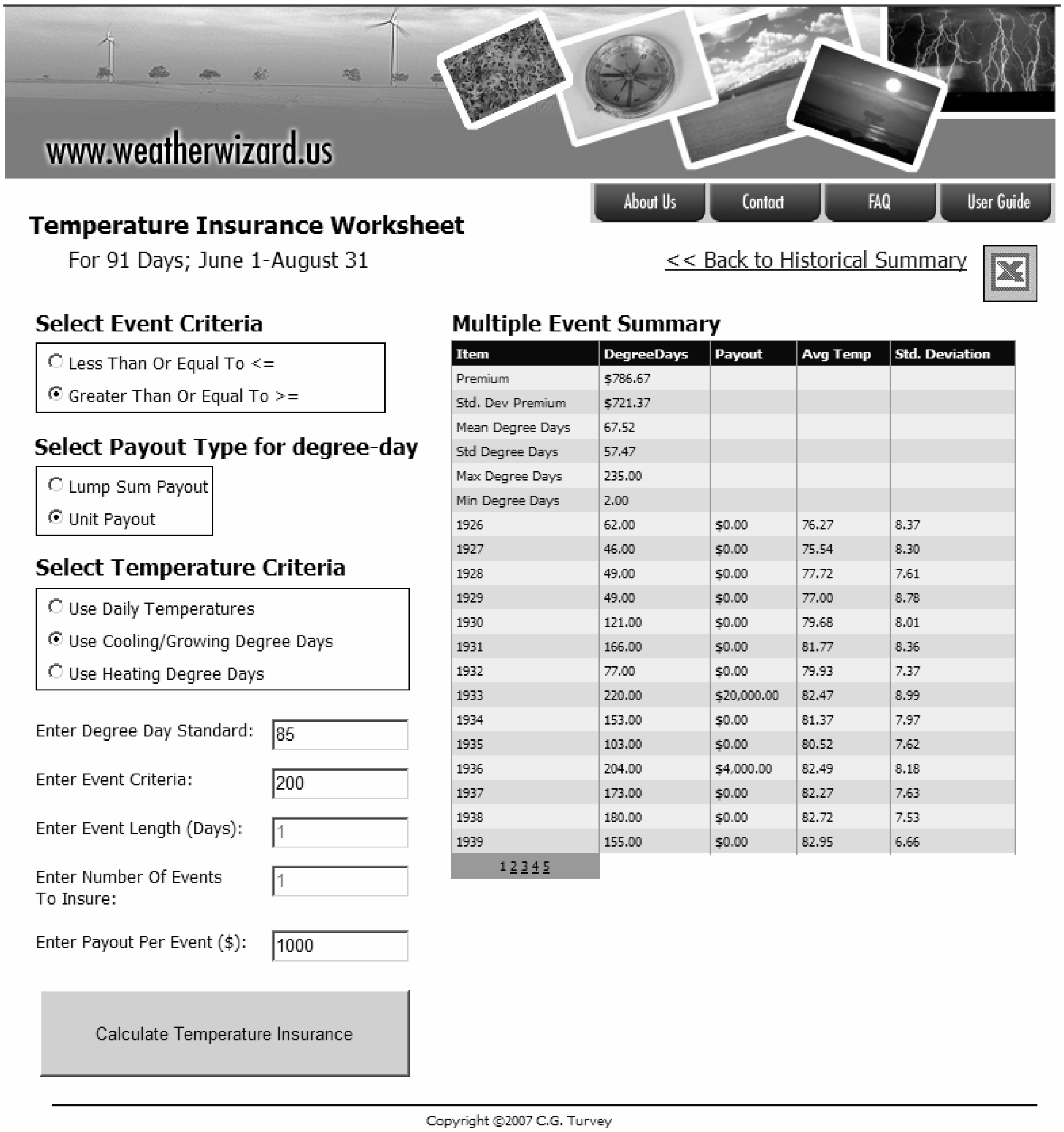


Figure A2. Date Selection Screen for Specific Event Risk

Note: Indicates that the user has selected daily high temperatures as the risk to be measured, at the Cornell Weather Station, using data from 1926 and 2001, and over the period June 1–August 31.



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Temperature Insurance Worksheet

For 91 Days; June 1-August 31

<< Back to Historical Summary

Select Event Criteria

- Less Than Or Equal To <=
- (selected) Greater Than Or Equal To >=

Select Payout Type for degree-day

- Lump Sum Payout
- (selected) Unit Payout

Select Temperature Criteria

- Use Daily Temperatures
- (selected) Use Cooling/Growing Degree Days
- Use Heating Degree Days

Enter Degree Day Standard: 85

Enter Event Criteria: 200

Enter Event Length (Days): 1

Enter Number Of Events To Insure: 1

Enter Payout Per Event ($): 1000

Calculate Temperature Insurance

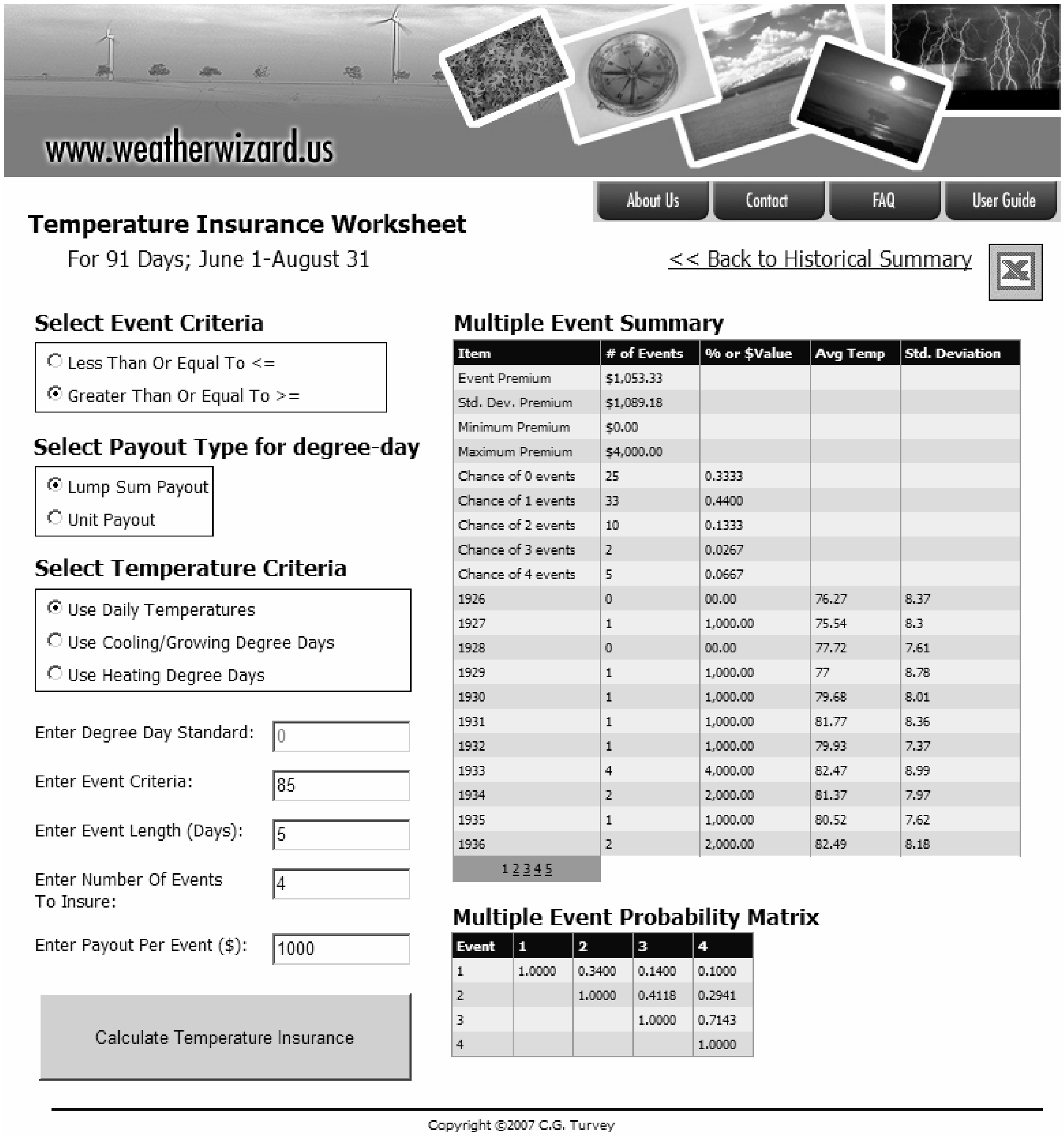
Multiple Event Summary

Item	DegreeDays	Payout	Avg Temp	Std. Deviation
Premium	$786.67			
Std. Dev Premium	$721.37			
Mean Degree Days	67.52			
Std Degree Days	57.47			
Max Degree Days	235.00			
Min Degree Days	2.00			
1926	62.00	$0.00	76.27	8.37
1927	46.00	$0.00	75.54	8.30
1928	49.00	$0.00	77.72	7.61
1929	49.00	$0.00	77.00	8.78
1930	121.00	$0.00	79.68	8.01
1931	166.00	$0.00	81.77	8.36
1932	77.00	$0.00	79.93	7.37
1933	220.00	$20,000.00	82.47	8.99
1934	153.00	$0.00	81.37	7.97
1935	103.00	$0.00	80.52	7.62
1936	204.00	$4,000.00	82.49	8.18
1937	173.00	$0.00	82.27	7.63
1938	180.00	$0.00	82.72	7.53
1939	155.00	$0.00	82.95	6.66

1 2 3 4 5

Figure A3. Temperature Insurance Worksheet

Note: Illustrates application of a degree-day excessive heat measure based on an 85°F standard, with strike of 200 degree-days, and a payout of $1,000/degree-day.



Multiple Event Summary

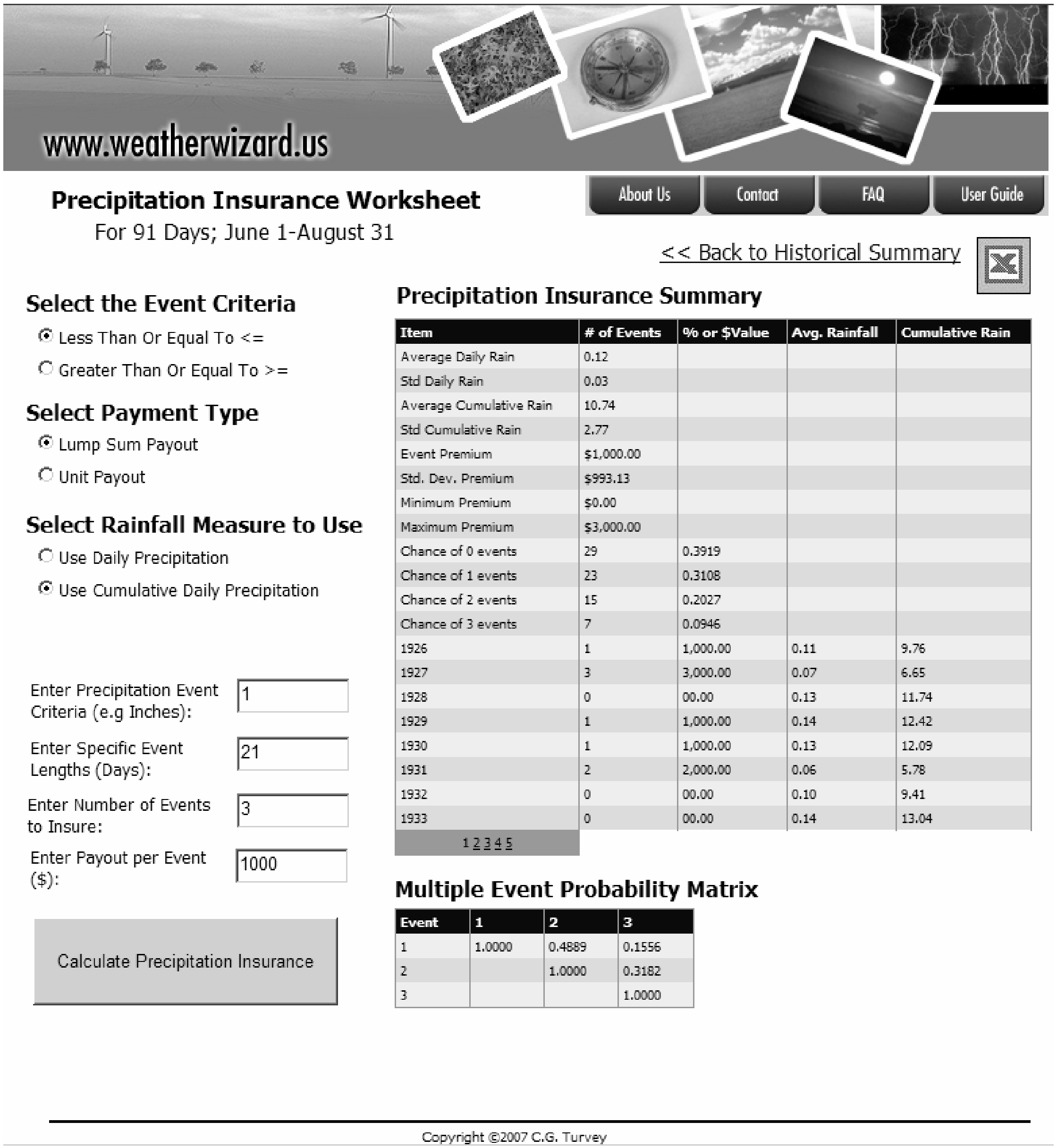
Item	# of Events	% or $Value	Avg Temp	Std. Deviation
Event Premium	$1,053.33			
Std. Dev. Premium	$1,089.18			
Minimum Premium	$0.00			
Maximum Premium	$4,000.00			
Chance of 0 events	25	0.3333		
Chance of 1 events	33	0.4400		
Chance of 2 events	10	0.1333		
Chance of 3 events	2	0.0267		
Chance of 4 events	5	0.0667		
1926	0	00.00	76.27	8.37
1927	1	1,000.00	75.54	8.3
1928	0	00.00	77.72	7.61
1929	1	1,000.00	77	8.78
1930	1	1,000.00	79.68	8.01
1931	1	1,000.00	81.77	8.36
1932	1	1,000.00	79.93	7.37
1933	4	4,000.00	82.47	8.99
1934	2	2,000.00	81.37	7.97
1935	1	1,000.00	80.52	7.62
1936	2	2,000.00	82.49	8.18

Multiple Event Probability Matrix

Event	1	2	3	4
1	1.0000	0.3400	0.1400	0.1000
2		1.0000	0.4118	0.2941
3			1.0000	0.7143
4				1.0000

Figure A4. Temperature Insurance Worksheet

Note: Illustrates excess heat risk above 85°F for four multiple events of six days in length, and the multiple event probability matrix.



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Precipitation Insurance Worksheet
For 91 Days; June 1-August 31

<< Back to Historical Summary

Select the Event Criteria
- (•) Less Than Or Equal To <=
- ( ) Greater Than Or Equal To >=

Select Payment Type
- (•) Lump Sum Payout
- ( ) Unit Payout

Select Rainfall Measure to Use
- ( ) Use Daily Precipitation
- (•) Use Cumulative Daily Precipitation

Enter Precipitation Event Criteria (e.g Inches): 1

Enter Specific Event Lengths (Days): 21

Enter Number of Events to Insure: 3

Enter Payout per Event ($): 1000

Calculate Precipitation Insurance

Precipitation Insurance Summary

Item	# of Events	% or $Value	Avg. Rainfall	Cumulative Rain
Average Daily Rain	0.12			
Std Daily Rain	0.03			
Average Cumulative Rain	10.74			
Std Cumulative Rain	2.77			
Event Premium	$1,000.00			
Std. Dev. Premium	$993.13			
Minimum Premium	$0.00			
Maximum Premium	$3,000.00			
Chance of 0 events	29	0.3919		
Chance of 1 events	23	0.3108		
Chance of 2 events	15	0.2027		
Chance of 3 events	7	0.0946		
1926	1	1,000.00	0.11	9.76
1927	3	3,000.00	0.07	6.65
1928	0	00.00	0.13	11.74
1929	1	1,000.00	0.14	12.42
1930	1	1,000.00	0.13	12.09
1931	2	2,000.00	0.06	5.78
1932	0	00.00	0.10	9.41
1933	0	00.00	0.14	13.04

1 2 3 4 5

Multiple Event Probability Matrix

Event	1	2	3
1	1.0000	0.4889	0.1556
2		1.0000	0.3182
3			1.0000

Figure A5. Precipitation Insurance Worksheet

Note: For Ithaca, NY, showing risk of cumulative rain in 21 days being less than 1 inch for up to three events and $1,000/event.